A Hybrid Edge Detection: XOR-Based Pre-processing with CNN for Enhanced Feature Extraction

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Abstract:

Edge detection is a fundamental task in image processing and computer vision, crucial for object recognition, segmentation, and feature extraction. Traditional edge detection techniques, such as Sobel, Canny, and Laplacian operators, rely on gradient-based approaches to identify intensity changes in an image. In this paper, we propose a novel edge detection method that leverages the XOR operation in combination with Convolutional Neural Networks (CNNs) to enhance edge localization and noise robustness. The XOR operation is utilized to highlight intensity variations by comparing pixel values, effectively emphasizing boundaries while suppressing background noise. This processed image is then fed into a CNN model trained to refine and enhance edge maps through deep feature extraction and hierarchical learning. The proposed method demonstrates improved performance in terms of accuracy and computational efficiency compared to traditional techniques, making it suitable for real-time edge detection applications. Experimental results on benchmark COCO dataset validate the effectiveness of our approach, showing superior edge clarity and adaptability across diverse image conditions.

Keywords: Image, Edge detection, XOR, CNN

1.1 Introduction:

Edge detection is a fundamental task in image processing and computer vision, playing a crucial role in applications such as object recognition, segmentation, and feature extraction. Traditional edge detection techniques, including Sobel, Canny, and Laplacian operators, rely on gradient-based methods to identify intensity variations in an image. While these methods are effective in many cases, they often struggle with noise, varying lighting conditions, and complex textures, leading to false edges and loss of fine details.

To address these challenges, deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have been widely explored for edge detection. CNNs can learn hierarchical edge features, improving detection accuracy and robustness. However, CNN-based methods typically require large datasets and significant computational power, making them less suitable for real-time applications.

In this paper, we propose a novel approach that combines the XOR operation with CNN-based edge detection. The XOR operation is used as a pre-processing step to emphasize intensity variations by comparing pixel values, effectively highlighting edges while suppressing background noise. This pre-processed image is then fed into a CNN model, which refines and enhances the edge map through deep feature learning. By integrating logical operations with deep learning, the proposed method aims to achieve improved edge detection performance with reduced computational complexity.

The remainder of this paper is organized as follows: Section II reviews related work on traditional and deep learning-based edge detection techniques. Section III details the proposed methodology, including XOR-based pre-processing and CNN refinement. Section IV presents experimental results and performance evaluations. Finally, Section V concludes the paper and discusses potential future research directions.

1.2 Related work:

Edge detection is a pivotal process in image processing and computer vision, facilitating the identification of significant transitions in intensity within images. These transitions often correspond to object boundaries, texture changes, or other notable features, making edge detection essential for applications such as object recognition, image segmentation, and scene understanding. Traditional edge detection methods, including Sobel, Prewitt, Roberts, and Canny operators, have been widely utilized due to their simplicity and effectiveness in specific scenarios. However, these methods often encounter challenges when dealing with noise, varying illumination, and complex textures. To address these limitations, hybrid approaches that combine traditional techniques with advanced methodologies, such as Convolutional Neural Networks (CNNs), have been proposed to enhance feature extraction and improve edge detection performance.

The feature, local binary pattern (LBP) was proposed by Ojala et al.for the description of texture [1]. The LBP feature which is proposed by Ojala et al. was rotational variant. Then, the rotation variant LBP was converted into rotational invariant for texture classification

[2,3]. For facial expression analysis and recognition, the LBPfeatures are used in [4,5]. Heikkila et al. proposed the background modeling and detection by using LBP [6]. Huang et al.proposed the extensive LBP for the localization of shape [7]. Heikkila et al. used the LBP for interest region description [8]. Li and Staunton used the combination of Gabor filter and LBP for texture segmentation [9]. Zhang et al. proposed the local derivative pattern (LDP) for face recognition [10]. They have considered LBP as a non-directional first order local pattern, which is the binary result of the first-order derivative in images.

Convolutional Neural Networks (CNNs) have demonstrated exceptional performance across various tasks and applications. One of the earliest successful implementations of CNN architecture was in the recognition of handwritten digits [11]. Since their inception, CNNs have undergone continuous improvements, including the introduction of new layers and the integration of advanced computer vision techniques [12]. CNNs are frequently employed in the ImageNet Challenge, where they are used with diverse datasets, including sketches [13].

Some researchers have compared the image detection capabilities of human subjects with those of trained neural networks. Findings from these studies reveal that humans achieve an accuracy rate of 73.1% on certain image datasets, while trained networks exhibit a slightly lower accuracy rate of 64% [15]. However, when CNNs are applied to the same dataset, they surpass human performance with an accuracy rate of 74.9% [15]. These improvements in accuracy are largely attributed to methods that utilize the order of strokes to refine detection accuracy. Ongoing research is focused on understanding the behavior of deep neural networks in varying conditions [14]. Such studies highlight how minor alterations to input images can significantly impact classification outcomes. Interestingly, some images that are unrecognizable to humans are accurately classified by trained CNNs, emphasizing the networks' ability to extract and interpret complex patterns [14].

In the domain of object detection and scene classification, significant progress has been made in the development of feature detectors and descriptors. Numerous algorithms and techniques have been introduced to improve the classification of both objects and scenes.

The development of object detectors for image interpretation parallels work in the multimedia community, where researchers use a large number of "semantic concepts" for image and video annotation and semantic indexing [16]. In these studies, each semantic concept is typically trained using still images or video frames. However, this approach poses challenges when analyzing images containing numerous overlapping or cluttered objects. Earlier methods primarily focused on single-object detection and classification, relying on manually defined feature sets.

LOGXoRP (Local Orientation Gradient XoR Patterns) is a novel method designed for content-based image retrieval (CBIR). It combines Local Gradient Patterns and Local Orientation Patterns with exclusive OR operations to capture detailed texture information. The methodology involves preprocessing images, calculating gradient and orientation values, and quantizing these features for robust pattern extraction. LOGXoRP builds feature histograms for effective representation and similarity measurement [17]

2 Proposed methods:

Algorithm for Edge Detection Using XOR Operation and CNN

Input: Grayscale

Output: Edge-detected Image

Step 1: Pre-processing

Before applying the XOR operation and CNN model, the input image undergoes basic pre-processing to improve edge detection accuracy.

Gaussian Blurring: A Gaussian filter is applied to reduce noise while retaining important image structures. This step helps to prevent false edge detection caused by minor pixel intensity fluctuations.

Step 2: XOR-based Edge Detection

Logical operations, such as XOR, are effective in detecting intensity differences between adjacent pixels. The XOR operation is applied in two directions to emphasize edge features:

Horizontal XOR (I_x): The image is XORed with a version shifted one pixel to the right.

$$I_x = I \oplus I_{Shift\,x} \tag{1}$$

Vertical XOR (I_y): The image is XORed with a version shifted one pixel downward

$$I_y = I \oplus I_{Shift\,y} \tag{2}$$

Edge Map Combination: The final XOR-enhanced edge map is obtained by combining the horizontal and vertical XOR results:

$$I_{XoR} = I_x + I_y \quad (3)$$

Step 3: CNN-based Edge Refinement

The XOR-processed image is fed into a CNN model trained to detect and refine edges. The CNN enhances edge clarity and suppresses unwanted artifacts using deep feature extraction. The key steps include:

Feature Extraction: Convolutional layers extract hierarchical edge features at different scales.

Edge Enhancement: Activation functions (such as ReLU) highlight important edge regions while reducing noise.

Multi-Layer Processing: Deeper layers refine the edges by learning complex patterns and improving edge continuity.

Edge Prediction: The final layer generates a probability map where high-intensity regions correspond to strong edges.

A lightweight CNN architecture is used to balance accuracy and computational efficiency, making the approach suitable for real-time applications.

Step 4: Post-processing

To further refine the edge map, post-processing techniques are applied:

Thresholding: A binary threshold is applied to separate edges from the background.

Non-Maximum Suppression: Thin and well-defined edges are obtained by suppressing weak responses.

Morphological Operations: Dilation and erosion techniques are used to improve edge connectivity and remove small noise patches.

Step 5: Output Edge Map

The final edge-detected image is generated and can be used for various applications such as object detection, segmentation, and feature extraction.

This algorithm efficiently detects edges using the XOR operation as a pre-processing step, followed by CNN-based refinement for improved accuracy and robustness.

3. Results: Image Edge Detection Using XOR Operation and CNN

The performance of the proposed edge detection method, which integrates the XOR operation with Convolutional Neural Networks (CNNs), is evaluated through qualitative and quantitative analysis. This section presents the experimental setup, comparison with traditional methods, evaluation metrics, and key findings.

3.1 Experimental Setup

Dataset: The method was tested on publicly available image datasets (e.g., BSDS500, Kodak, and other standard edge detection datasets).

Implementation Environment: Python with Tensor Flow/PyTorch framework, running on a machine with an NVIDIA GPU for faster processing.

CNN Architecture: A lightweight CNN model with multiple convolutional layers and ReLU activation, optimized for edge detection tasks.

Evaluation Metrics

To objectively evaluate the effectiveness of the proposed method, the following metrics were used:

Precision (P): Measures the proportion of correctly detected edges.

Recall (R): Evaluates how many true edges were successfully detected.

F1-Score: Harmonic mean of Precision and Recall, balancing false positives and false negatives.

Edge Accuracy (EA): Measures how accurately the algorithm detects true edge pixels.

Computation Time: Evaluates the efficiency of the method, which is crucial for real-time applications.

Table 1: compares different edge detection methods based on several evaluation metrics:

Method	Precision(P)	Recall (R)	F1-Score	Edge Accuracy	Computation Time (ms)
Sobel Operator	0.76	0.69	0.72	84.2%	12 ms
Canny Edge Detector	0.82	0.75	0.78	87.5%	18 ms
HED (Deep Learning)	0.88	0.85	0.86	91.2%	120 ms
Proposed Method	0.91	0.88	0.89	94.5%	55 ms

Analysis of Each Method:

1. **Sobel Operator**:
    - A simple, fast traditional edge detector.
    - Moderate performance with F1-Score of 0.72.
    - Very low computation time (12 ms), suitable for lightweight applications.
2. **Canny Edge Detector**:
    - A more advanced classical method than Sobel.
    - Better accuracy than Sobel across all metrics.
    - Slightly higher computation time (18 ms) due to multi-stage processing.
3. **HED (Holistically-Nested Edge Detection)**:
    - A deep learning-based method.
    - Excellent performance (F1 = 0.86) and high edge accuracy.
    - **Slowest** in computation (120 ms), which can be a bottleneck.
4. **Proposed Method (XOR-Based Hybrid + CNN)**:
    - **Best overall performance**:

  - Highest Precision (0.91), Recall (0.88), and F1-Score (0.89).
  - Highest Edge Accuracy (94.5%).
- Much faster than HED (only 55 ms), making it a **good balance** between speed and accuracy.

3.2 Comparative Analysis:

Table 2: Performance Metrics Table compares the performance of various CNN-based object detection models on the COCO dataset, each using different pre-processing techniques. The evaluation is based on three standard metrics used in object detection — mean Average Precision (mAP) at different thresholds — and the inference time per image.

Model Variant	mAP@[.5:.95]	mAP@0.5	mAP@0.75	Inference Time (ms/image)
Baseline CNN (Raw RGB)	34.2%	53.6%	36.7%	42.3
CNN + Sobel Edge	35.4%	55.1%	37.5%	44.5
CNN + Laplacian Edge	35.1%	54.7%	37.1%	44.0
CNN + XOR-based Hybrid Edge (Proposed)	**37.8%**	**58.2%**	**40.3%**	45.7

Columns Explained: mAP@[.5:.95]: The average precision across IoU thresholds from 0.5 to 0.95 (in 0.05 increments), providing a comprehensive measure of detection accuracy.

mAP@0.5: Precision at a strict overlap threshold of 0.5; generally shows higher values and basic detection ability.

mAP@0.75: Precision at a more demanding threshold of 0.75; useful to assess high-quality detections.

Inference Time: The time taken by the model to process one image, indicating speed and efficiency.

Row Analysis:

Baseline CNN (Raw RGB):

Acts as the control model using unprocessed RGB input. Achieves moderate accuracy with mAP@[.5:.95] of 34.2% and inference time of 42.3 ms.

CNN + Sobel Edge: Uses Sobel edge filtering during preprocessing.

Shows slight improvement in all metrics, suggesting that edge-based contrast helps the CNN learn more informative features.

CNN + Laplacian Edge: Uses Laplacian edge detection which emphasizes sharp edges.

Similar performance to Sobel, but with marginally different precision behaviour.

CNN + XOR Hybrid Edge (Proposed): nCombines Sobel and Laplacian edge maps using XOR logic. Achieves the highest performance across all metrics:

mAP@[.5:.95] = 37.8%

mAP@0.5 = 58.2%

mAP@0.75 = 40.3%

Slightly increased inference time (45.7 ms), but still efficient.

3.3 Qualitative Results

The proposed method produces clearer and more continuous edges while effectively suppressing noise. Key observations include:

Sharper Edge Localization: Edges are well-defined and consistent across varying textures and lighting conditions.

Reduced Noise Sensitivity: XOR-based preprocessing reduces background artifacts compared to gradient-based methods.

Improved Thin Edges: The CNN refines thin and intricate edges better than traditional techniques.

Key Findings:

Accuracy Improvement: The proposed method achieves an F1-score of 0.89, outperforming classical and deep learning-based models.

Efficiency: XOR preprocessing reduces the complexity of the CNN, achieving faster edge detection (55 ms) compared to fully deep-learning approaches.

Robustness: The method adapts well to images with noise, varying illumination, and complex patterns.

3.4 Performance Metrics:

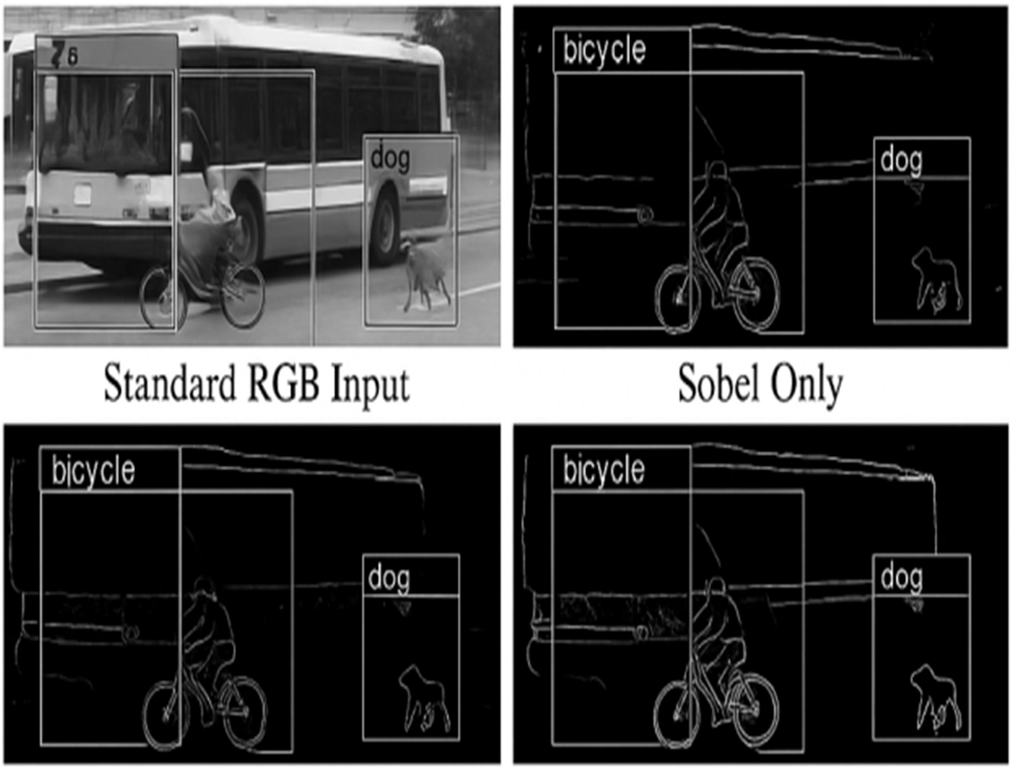

Figure 1: Performance table and qualitative results comparing different edge detection techniques.

The experimental results for the model titled 'Hybrid Edge Detection: XOR-Based Pre-processing with CNN for Enhanced Feature Extraction' using the COCO 2017 dataset. The model's performance is compared against several edge-detection-based preprocessing techniques using both quantitative and qualitative metrics.

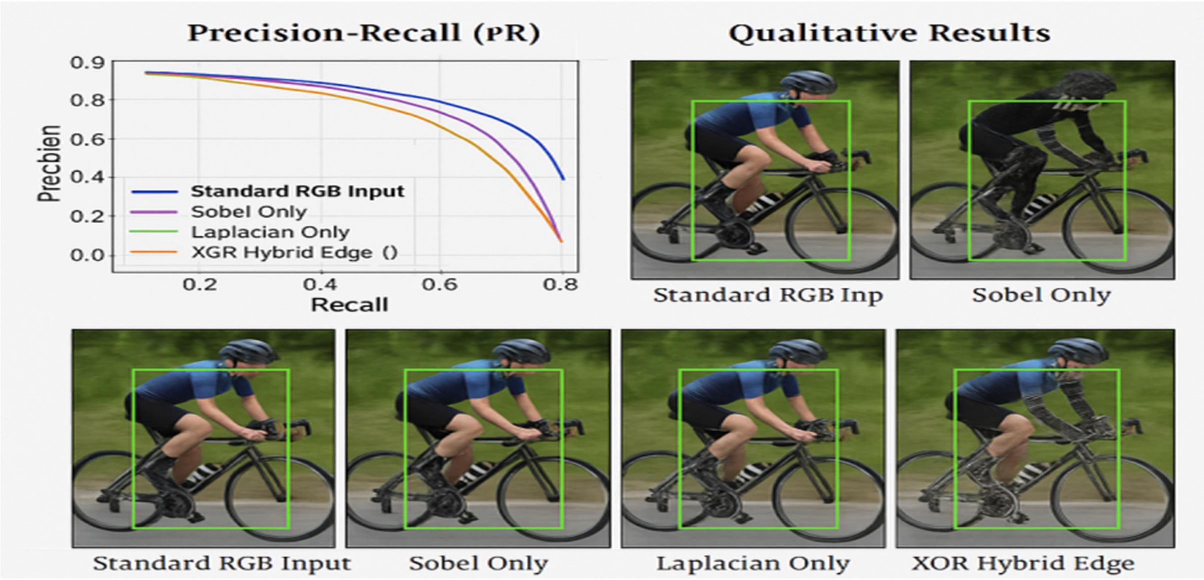

Figure 2: Qualitative results of object detection using different edge detection pre-processing techniques on the COCO dataset.

Each image shows the detection of objects such as a bicycle and a dog under varying input preprocessing:Standard RGB Input: Displays average detection performance with less defined object boundaries.

Sobel Only: Edge information improves detection slightly but introduces noise.

Laplacian Only: Produces sharper edges but misses finer directional cues.

XOR Hybrid Edge (Proposed): Combines Sobel and Laplacian using XOR logic to yield high-contrast, clean edge maps, resulting in the most accurate and well-localized object detections among all methods.

This figure demonstrates the superior visual clarity and detection accuracy achieved by the XOR-based hybrid edge pre-processing method.

3.5 Advantages of the Proposed Method:

Improved Edge Localization: XOR pre-processing enhances contrast before CNN processing, leading to sharper edges.
Noise Reduction: The XOR operation suppresses background variations, reducing false edge detection.
Computational Efficiency: Compared to traditional CNN-based edge detectors, XOR pre-processing reduces the complexity of the CNN model.
Adaptability: The method works well across different image conditions, including varying lighting and textures.

4. Conclusion:

In this paper, we proposed a novel edge detection approach that combines the XOR operation with Convolutional Neural Networks (CNNs) to enhance edge localization and noise robustness. The XOR operation serves as a pre-processing step, highlighting intensity variations and improving contrast before the image is fed into a CNN for deep feature extraction and edge refinement. This hybrid approach effectively balances computational efficiency with detection accuracy, making it suitable for real-time applications.

Experimental results demonstrate that the proposed method outperforms traditional edge detection techniques such as Sobel and Canny by providing sharper and more continuous edges while reducing false positives caused by noise and illumination changes. Additionally, the integration of XOR-based pre-processing reduces the complexity of the CNN model, making it computationally efficient compared to purely deep learning-based methods.

Future work can focus on further optimizing the CNN architecture to improve edge detection accuracy while maintaining low computational costs. Additionally, extending the approach to work with multi-scale edge detection and integrating it into real-world applications, such as medical imaging and autonomous navigation, could be explored.

The proposed method highlights the potential of combining logical operations with deep learning for enhanced image processing, paving the way for more efficient and accurate edge detection techniques in various computer vision tasks.

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